Short-Term Day-Ahead Hydrothermal Scheduling with Variable Renewables, Storage, Load Shedding using Artificial Intelligence Techniques for Demand Forecasting

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***Abstract*— Short-Term Hydrothermal Scheduling (STHS) is a very complex, multimodal, nonlinear optimization problem that has primarily been addressed by conventional and, more recently, metaheuristic optimization algorithms. The objective of conventional STHS is to optimize the hourly energy production of hydroelectric power plants and other generation sources over a specific period of time, allowing for the determination of the optimal economic operation of the Power Electrical System (PES). The conventional STHS formulation is widely used in the planning, analysis and operation of PES. However, nowadays PES incorporate variable renewable generation such as wind and solar photovoltaic power, as well as Energy Storage Systems (ESS), transmission grid models and load shedding scenarios in case of possible operational contingencies. This paper presents a STHS formulated and simulated using nonlinear programming for a day ahead, using artificial neural networks (ANN) for demand forecasting. The integration of wind and solar photovoltaic generation, ESS and cascaded hydroelectric power plants is considered, along with the transmission grid and load shedding models, all within a single optimization problem. The objective is to minimize generation costs and optimize power usage, dispatching the units in the most efficient manner. The efficient assignment of thermal, hydro, solar, wind units and ESS allows for optimal use of available water without exceeding reservoir limits. The formulation is validated using the IEEE 30-node system, obtaining optimal solutions in all scenarios, without the need to relax system constraints for convergence.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9632

Index Terms*— *Short-term hydrothermal scheduling, economic dispatch, nonlinear scheduling, load shedding, energy storage systems, variable renewables.

I. Introduction

THE purpose of conventional Short-Term Hydrothermal Scheduling (STHS) is to maximize the efficiency of electric power generation in the hydroelectric and thermal plants over a specified period, leading in the optimal economic operation of the Power Electrical System (PES). This is achieved by minimizing the cost of thermal unit operation through the optimal utilization of available water from hydroelectric reservoirs while simultaneously satisfying load demands and various constraints in both hydro and thermal systems. STHS typically covers a time period ranging from one day to one week in advance. Generally, a PES consist of different types of generation, commonly thermoelectric and hydroelectric. However, the current trend is to integrate solar, wind generation along with Energy Storage Systems (ESS). Additionally, modern systems incorporate transmission network models and load-shedding scenarios to account for potential operational contingencies, which extend beyond the conventional STHS model. The economic operation of the system is determined by the coordination of these different generation sources [1]. Therefore, it is necessary to incorporate the respective mathematical models and the associated constraints of the above into the STHS model in a single optimization problem, which reflects the actual conditions of the STHS. The main aspect that differentiates the coordination of hydropower plants is the presence of numerous constraints, such as water discharges, which may be regulated by political, environmental or economic factors and are reflected in laws and treaties [2]. In Mexico, the STHS is carried out by the Independent System Operator (ISO), the National Energy Control Center (CENACE), which is responsible for the operational control of the Mexican PES at the extended horizon unit commitment stage (AUHE) for a period of one week in advance. Additionally, incorporating variable wind and solar generation, load shedding, energy storage systems, and the transmission grid into the mathematical model makes the STHS optimization problem even more complex. These additional factors often lead to non-convergence in the search for an optimal solution, as they are not considered in the conventional STHS model.

II. State of Art

In [3], electricity demand forecasting is conducted by an Artificial Neural Network (ANN). The ANN is trained from two years of data (17520 hours of operation/supply) of the Mexican National Electric System (SEN).

In [4], a comprehensive literature review of the STHS problem over the last four decades is presented. The authors review more than 300 studies classifying them into conventional methods and metaheuristic methods. Among the

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traditional methods, Lagrangian Relaxation, Mixed Integer Programming (MIP) and Dynamic Programming (DP) stand out. Among the metaheuristic methods, Particle Swarm Optimization (PSO) is the most prominent, as it has the largest number of publications, [5], [6]. Other notable metaheuristic approaches include Evolutionary Programming (EP) [7],[8], Cuckoo Search Optimization Algorithms (CSA), Gravitational Search (GSA), Genetic Algorithms (GA), [9], [10], which require a large number of iterations compared to other metaheuristic algorithms.

Additionally, since most of these methods are based on swarm intelligence such as bee colonies, ant colonies, grasshopper swarms, and wolf packs many variants have achieved better results in terms of convergence speed [11]–[18]. However, the authors noticed that algorithms based on harmonic search and biogeography converged more slowly [4].

In [2], a metaheuristic algorithm called Grey Hybrid Wolf Optimizer and Cuckoo Search (HGWOCS), is applied to solve the STHS problem in a hybrid power system. This system consists of conventional thermal power generation, hydro plants, wind farms, and solar power plants but does not include the transmission network or several constraints related to the hydro and thermal systems.

A method based on the Lagrange multiplier theory for solving the optimal scheduling of a STHS is presented in [19]. The authors determine the water discharge in the first interval, resulting in a low number of iterations and a short computational time to achieve convergence.

In [19], an integrated hydraulic model with a reservoir system and gas constraints is presented using mixed-integer linear programming (MILP) and the branch and bound & cut (BB&C) algorithm to perform a STHS. The methodology linearizes the startup/shutdown cost curve and considers the gas constraints of the thermal units. It is tested on large scale simulations of 300, 777 and 4995 nodes, but does not include the transmission network.

In [20], a mixed-integer programming (MIP) formulation of logarithmic size is proposed to address the challenge of handling a high number of variables and constraints due to term linearization. Specifically, it requires only a logarithmic number of binary variables and constraints to segment and linearize the nonlinear functions.

In [21], nonlinear dynamic programming is introduced to obtain the STHS. The authors consider the impact of the load at the valve point of conventional thermal units and the power transmission loss of the system by studying two test systems.

Particle Swarm Optimization algorithms (PSO) are widely studied, offering near-optimal solutions and robust solutions in other cases. They perform well on low-dimensional and high-dimensional STHS problems, with a high convergence rate, especially in variants such as APSO, quantum PSO and dynamic search PSO. Improving exploration and exploitation variables, such as alpha and beta, could help prevent premature convergence to local optima [22]–[24].

Cuckoo search algorithms (CSA) generally conclude that a good approximation to the global optimal solution has been achieved. They typically promise fast convergence, but many PSO variants performed better in convergence [4], [25]–[29].

Gravitational search algorithms (GSA) usually provide solutions close to the global optimum or robust solutions, with a good convergence rate, especially with chaotic mutations. Their structure is similar to PSO variants, and the results are comparable in most implementations [30], [31].

Of all the papers reviewed in the above publications, the test system and STHS models vary widely, e.g; several studies consider only one hydro plant, most do not consider cascade systems and many include only a few thermal units. Additionally, many do not incorporate several thermal system constraints such as up/down ramping rate, or the transmission grid. Furthermore, some studies do not consider additional renewable generation, such as wind and solar or ESS, and their impact on the STHS. Many also neglect load shedding and focus mainly on the convergence rate of the method employed. This variability makes it difficult to objectively compare the efficiency of one study with another.

A. Contribution

In this paper, to find the solution to the STHS, the following approach is proposed; first the demand is predicted using neural networks for a day ahead, and the demand profile is normalized to apply it to our test system. Subsequently, the STHS is performed through communication between Matlab and GAMS softwares, with GAMS being the software used to find the optimal solution of these optimization problems. The main contributions of this work are as follows:

- The demand profile of the system is obtained using real data of two years of the Mexican PES, as provided by the ANN proposed in [3]. This allows us to obtain the load profile, which in turn enables us to formulate and solve the STHS with greater precision, using a technique for which there is limited evidence in the literature regarding the application of ANN to the STHS problem.
- A STHS that incorporates variable wind and solar generation with different degrees of penetration, cascaded hydroelectric power plants, ESS, load shedding, and the transmission grid, is proposed and applied to the IEEE 30-node system.
- The implementation of all of the above in a single optimization problem, finding the optimal solution for all cases and ensuring the method converges without the need to relax system constraints, is not commonly seen in the literature. This leads to a more realistic integration of renewables, ESS, and cascaded power plants, along with their economic impact on the system. There is limited evidence in the literature on how STHS is achieved by considering all these factors.

III. Neural Network for Demand Forecasting

ANNs offer an alternative to conventional techniques, with their importance lying in their application to solve problems that, prior to their development, could not be addressed by traditional methods. These conventional techniques are usually limited by strict assumptions of normality, linearity, variable independence, and limited or no adaptability [32], [33]. ANNs are a relatively common option and have been shown to be highly accurate methods for Demand Forecasting (DF) [34]. The literature demonstrates that classical methods can no longer give dominant results for DF [35].

A. ANN for Demand Forecasting

The electric demand forecasting (DF) is performed using Artificial Intelligence (AI), with an Artificial Neural Network (ANN) as the technique. The training algorithm used was Bayesian Regulation. The ANN is created from 2 years of data (17520 hours of operation/supply) of the Mexican National Electric System (SEN), obtained from the Mexican ISO, CENACE. To improve the network accuracy, an exhaustive filtering of the raw data for outliers was conducted. This ANN is explained in detail in [3].

IV. Formulation of the STHS Problem

A. Conventional STHS Model

Mathematically, the short-term hydrothermal coordination model is [36]:

$$min\ (C_T) = \sum_{t=1}^{T}\sum_{g=1}^{Ng} a_g\left(Pg_{g,t}\right)^2 + b_g(Pg_{g,t}) + c_g + \sum_{t=1}^{T}\sum_{i=1}^{Nh} Ch_i\,(Ph_{i,t}) \quad (1)$$

$$\sum_{t=1}^{T}\sum_{g=1}^{Ng}\left(Pg_{g,t}\right) + \sum_{t=1}^{T}\sum_{i=1}^{Nh}(Ph_{i,t}) = \sum_{t=1}^{T}(Pd_t) \quad (2)$$

$$Ph_{i,t} = f_i\left(Vol_{i,t}, q_{i,t}\right) = -c1_i Vol_{i,t}^2 - c2_i q_{i,t}^2 + c3_i Vol_{i,t} q_{i,t} + c4_i Vol_{i,t} + c5_i q_{i,t} + c6_i S_{i,(t+1)} \quad (3)$$

$$Vol_{i,(t+1)} = Vol_{i,t} + \sum_{i=1}^{Nh}\left[q_{i,(t-\tau)} + S_{i,(t-\tau)}\right] - q_{i,(t+1)} - S_{i,(t+1)} + r_{i,(t+1)} \quad (4)$$

$$Vol_i^{min} \le Vol_{i,t} \le Vol_i^{max} \quad (5)$$
$$q_i^{min} \le q_{i,t} \le q_i^{max} \quad (6)$$
$$Pg_g^{min} \le Pg_{g,t} \le Pg_g^{max} \quad (7)$$
$$Ph_i^{min} \le Ph_{i,t} \le Ph_i^{max} \quad (8)$$
$$0 \le S_{i,t} \le S_i^{max} \quad (9)$$
$$Vol_{i,0} = Vol_i^{initial} \quad (10)$$
$$Vol_{i,24} = Vol_i^{end} \quad (11)$$

where C_T is the total generation cost (objective function), a_g, b_g, c_g are the coefficients of the cost curve of thermal generator i, $Ch_i\left(Ph_{i,t}\right)$ is the cost of generation for each hydroelectric generator i at time t, $Pg_{g,t}$ is the thermal power generation for each generator g at time t, $Ph_{i,t}$ he power generated by hydroelectric generator i at time t, and Pd_t is the active power demand at time t. Pg_g^{Min}, Pg_g^{Max} are the power limits of each generator g, $q_{i,t}$ is the flow rate of the hydroelectric unit i at time t in m^3/h, $Vol_{i,t}$ is the volume of water in the reservoir i at time t in m^3, $r_{i,t}$ is the inflow (input) of the hydroelectric unit i at time t in m^3/h, $S_{i,t}$ is the spill from the hydroelectric unit i at time t in m^3/h, τ_i is the delay of the hydroelectric unit i to the plant immediately downstream (if there is one), and [$c1_i$, $c2_i$, $c3_i$, $c4_i$, $c5_i$, $c6_i$] are known constants for each hydroelectric unit i. Spills $S_{i,t}$ are typically considered to be 0 if there are none.

V. Incorporating the Transmission Grid, Variable Renewable Generation, Storage Systems and Load Shedding into the STHS Model

A. Transmission Grid

When incorporating the transmission grid, it is necessary to include the power flow constraints, voltage and nodal angle restrictions, maximum transmittable power on transmission lines, ramp-up and ramp-down limits of thermal generators, a connectivity matrix that associates system generators with their respective nodes, and the reactive power equation along with its generator limits.

Specifically, the following term is added to the left-hand side of Equation (2):

$$-\sum_{\substack{ij,t \\ i\neq j \\ j\in i}}^{Nn} P_{ij,t}$$

The following equations and constraints are added:

$$\sum_{g,t}^{Ng} Qg_{g,t} - \sum_{i,t}^{Nn} Qd_{i,t} = \sum_{\substack{ij,t \\ i\neq j \\ j\in i}}^{Nn} Q_{ij,t} \quad (12)$$
$$P_{ij,t} = V_{i,t}\sum_{j\in i}^{Nn} V_{j,t}\, Y_{ij}\cos\left(\theta_{i,t} - \theta_{j,t} - \gamma_{ij}\right) \quad (13)$$
$$Q_{ij,t} = V_{i,t}\sum_{j\in i}^{Nn} V_{j,t}\, Y_{ij}\sin(\theta_{i,t} - \theta_{j,t} - \gamma_{ij}) \quad (14)$$
$$Pg_{g,t} - Pg_{g,t-1} \le \mathrm{RU}_g \quad (15)$$
$$Pg_{g,t} - Pg_{g,t-1} \le \mathrm{RU}_g \quad (16)$$
$$P_{ij} \le P_{ij}^{Max} \quad (17)$$
$$Qg_g^{Min} \le Qg_g \le Qg_g^{Max} \quad (18)$$
$$V_i^{Min} \le V_i \le V_i^{Max} \quad (19)$$
$$\theta_i^{Min} \le \theta_i \le \theta_i^{Max} \quad (20)$$

where $Q_{ij,t}$ is the reactive power flow calculated from node i to node j at time t, $Qg_{g,t}$ is the reactive power generated by generator g at time t, $Qd_{i,t}$ is the reactive power demand at node i at time t. The limits of reactive power generation for each generator g are given by Qg_g^{Min} and Qg_g^{Max}. V_i and V_j represent the voltage magnitudes at nodes i and j, respectively, while V_i^{Min} and V_i^{Max} denote the voltage limits at node i. Similarly, θ_i is the voltage angle at node i, with θ_i^{Min} and θ_i^{Max} representing its nodal angular limits. Y_{ij} and γ_{ij} correspond to the magnitude and angle of element ij in the nodal admittance matrix $Ybus$. The active power flow in the transmission line connecting nodes i and j at time t is given by $P_{ij,t}$, while P_{ij}^{Max} represents the limit of the active power flow in the transmission line. Finally, RU_g and RD_g denote the ramp-up and ramp-down limits of thermal generator g, respectively.

B. Variable Wind and Solar Power Generation

Wind and solar power generation forecast data is obtained from the Mexican ISO. The terms associated with the cost of wind and solar power plants are added to equation (1):

$$\sum_{wg,t}^{nw} Cw_{wg}\left(PW_{wg,t}\right) + \sum_{sg,t}^{ns} Cs_{sg}\left(PS_{sg,t}\right) \quad (21)$$

The terms associated with the active power generated by these power plants are incorporated into equation (2):

$$+\sum_{\substack{w,t\\ w\in i}}^{nw} PW_{w,t} + \sum_{\substack{s,t\\ s\in i}}^{ns} PS_{s,t} \quad (22)$$

The following equations and constraints are also introduced:

$$PW_i^{Min} \le PW_{w,t} \le PW_i^{Max} \quad (23)$$

$$0 \le PS_{s,t} \le PS_s^{Max} \quad (24)$$

where Cw_{wg} and Cs_{sg} are the cost coefficients associated with wind and solar generators, respectively. $PW_{w,t}$ and $PS_{s,t}$ represent the active power generated by wind and solar power plants. The active power limits of wind and solar generators are given by PW_w^{Max} and PW_i^{Min}respectively.

C. Energy Storage System

To incorporate the ESS, it is necessary to introduce the following equations and terms related to ESS charging and discharging, the associated costs, the State Of Charge (SOC), ESS operational limits, and maximum transmittable charge/discharge power, i.e. [37]:
The cost-related terms are incorporated to equation (1):

$$\sum_{e,t}^{nE} Cchr_e\left(Pchr_{e,t}\right) + \sum_{e,t}^{nE} Cdis_e\left(Pdis_{e,t}\right) \quad (25)$$

The terms associated with active power are incorporated to equation (2):

$$-\sum_{\substack{e,t\\ e\in i}}^{nE} Pchr_{e,t} + \sum_{\substack{e,t\\ e\in i}}^{nE} Pdis_{e,t} \quad (26)$$

The following equations and constraints are introduced:

$$SOC_{e,t} = SOC_{e,t-1} + \frac{\Delta t}{E_e^{cap}}\{\eta_{chr} Pchr_{e,t} - \frac{Pdis_{e,t}}{\eta_{dis}}\} \quad (27)$$

$$SOC_e{}^{Min} \le SOC_e(t) \le SOC_e{}^{Max} \quad (28)$$

$$Pchr_e^{Min} \le Pchr_{e,t} \le Pchr_e^{Max} \quad (29)$$

$$Pdis_e^{Min} \le Pdis_{e,t} \le Pdis_e^{Max} \quad (30)$$

$$SOC_{e,t0} = SOC_{e,T} \quad (31)$$

where $Pchr_{e,t}$ and $Pdis_{e,t}$ represent the charging and discharging power of the *ESS* at time t, respectively. $Cchr_e$ and $Cdis_e$ are the costs associated with charging and discharging the ESS. η_{chr} and η_{dis} denote the charging and discharging efficiency of the ESS. E_e^{cap} represents the ESS capacity, and $SOC_{e,t}$ is the state of charge of the ESS eat time t. $SOC_{e,t0}$ and $SOC_{e,t\,T}$refer to the initial and final state of charge of the ESS. $SOC_e{}^{min}$ and $SOC_e{}^{max}$ define the permissible SOC limits, which typically range between 0 and 1. In general, the initial and final SOC are expected to be equal [37].

D. Load Shedding

If in any scenario while solving the STHS, there is insufficient generation to supply the demand, the problem becomes infeasible, and no solution can be found. In such cases, it is necessary to implement Load Shedding (LSH) to avoid this scenario [38]. The LSH is modeled using a virtual generator connected to node *i*, which is added in equation (2). The production cost of this unit is set to a high value and added to equation (1), usually referred to as the Value Of Loss Load (VOLL). The “generation” level of this unit is equal to the load loss that should occur at node *i*. The maximum power of this unit is equal to the load connected to node *i*, equation (34). Mathematically, this is represented as:

$$\sum_{i,t}^{Nn} LS_{i,t}, \quad t = 1,2,3 \ldots T \quad (32)$$

$$\sum_{i,t}^{Nn} VOLL \cdot LS_{i,t}, t = 1,2,3 \ldots T \quad (33)$$

$$0 \le LS_{i,t} \le Pd_{i,t} \quad (34)$$

VI. Short-Term Day-Ahead Hydrothermal Scheduling with Variable Renewables, Storage, Load Shedding, Implementing Artificial Neural Networks for Demand Forecasting

Once the DF is obtained using the ANN, it is normalized and applied to our test system over a 24-hour forward horizon. The test system used to evaluate the STHS is the IEEE 30-node case. The system consists of six thermal generators with a total generation capacity of 335 MW and 41 transmission lines. It is modified to incorporate cascaded hydroelectric power plants to node 4, three photovoltaic power plants connected to nodes 3, 4 and 6, three wind power plants connected to nodes 1, 13 and 22, an energy storage system connected to node 7, and the load shedding model. The modified IEEE 30-node test system is provided in the appendix.

Each type of generator is associated with node i according to a connectivity matrix, in case multiple generators are connected to the same node. It is worth noting that the cost of wind and solar photovoltaic plants may be zero since they do not consume fuel; however, their total cost is not zero, as it includes operation, maintenance, and return on investment.

The proposed system is tested in three case studies with the following considerations:

- A 24-hour time horizon with hourly time periods (24 time steps).
- The penalty cost for load shedding is set to 10,000 \$/MW.
- A flat voltage profile of $1\angle 0°$, is assumed at the start of the iterative process.
- Voltage constraints are set to $\pm$5% in per unit (p.u.), and the angular constraints to $\pm$ 90º.
- The total system demand is 3,769.326 MW.

Case study data are imported from Matlab and Excel into GAMS, which is used to find the optimal solution by nonlinear programming (NLP) using the CONOPT4 solver. Generator data by type of technology and system specifications can be found in the appendix. The ESS data are provided in Table I.

A. *Study Case 1*

Case 1 serves as the baseline for comparison. It includes all the system components described previously but does not incorporate optimization in its solution. As a result, any solution that satisfies the imposed equations and constraints is considered valid, since there is no objective function to optimize.

B. *Study Case 2*

Case 2 represents our operational scenario for comparison. It includes all system components and validates:

- The correct implementation of the STHS model.
- Convergence by finding the optimal solution.
- The impact of different generation sources on system operation, ensuring no load shedding occurs.
- Variations in local marginal prices (LMP).
- The effect of the energy storage system (ESS) under normal operating conditions.

C. *Study Case 3*

The key difference between case 2 and 3 is that in case 3 the demand is increased by a factor of 2.5 compared to case 2. This increase leads to an insufficient generation capacity and congestion in the transmission lines, making load shedding necessary. The objective is to validate system convergence by finding the optimal solution in a load shedding scenario.

VII. Experimental Results

The results of the optimal solution obtained from the STHS for the 30-node system in the three cases are presented below.

- Case 1: Since there is no optimization criterion and no objective function to optimize, any solution that satisfies the imposed equations and constraints is considered valid.
- Cases 2 and 3: When finding the optimal solution, all variables remain within their operating limits.
- Case 3: Due to insufficient generation and transmission line overload, load shedding is applied to maintain system feasibility.

TABLE I
Energy Storage System Data

Parameter	P^{dis}_{max} MW	P^{dis}_{min} MW	P^{chr}_{max} MW	P^{chr}_{min} MW	η_{chr} Charge	η_{dis} Discharge
Value	13.4	0	13.4	0	95 %	90 %

TABLE I (CONTINUATION)
Energy Storage System Data

Parameter	Capacity (MW)	SOC_0 MW	\$/MW Charge	\$/MW Discharge
Value	67	13.4	0.2	0.1

Fig. 1 shows the generation by type of technology, for each case. Fig. 1a shows that despite having cheaper generation available to supply demand, hydroelectric, solar and wind generation come into operation only in a few time intervals.

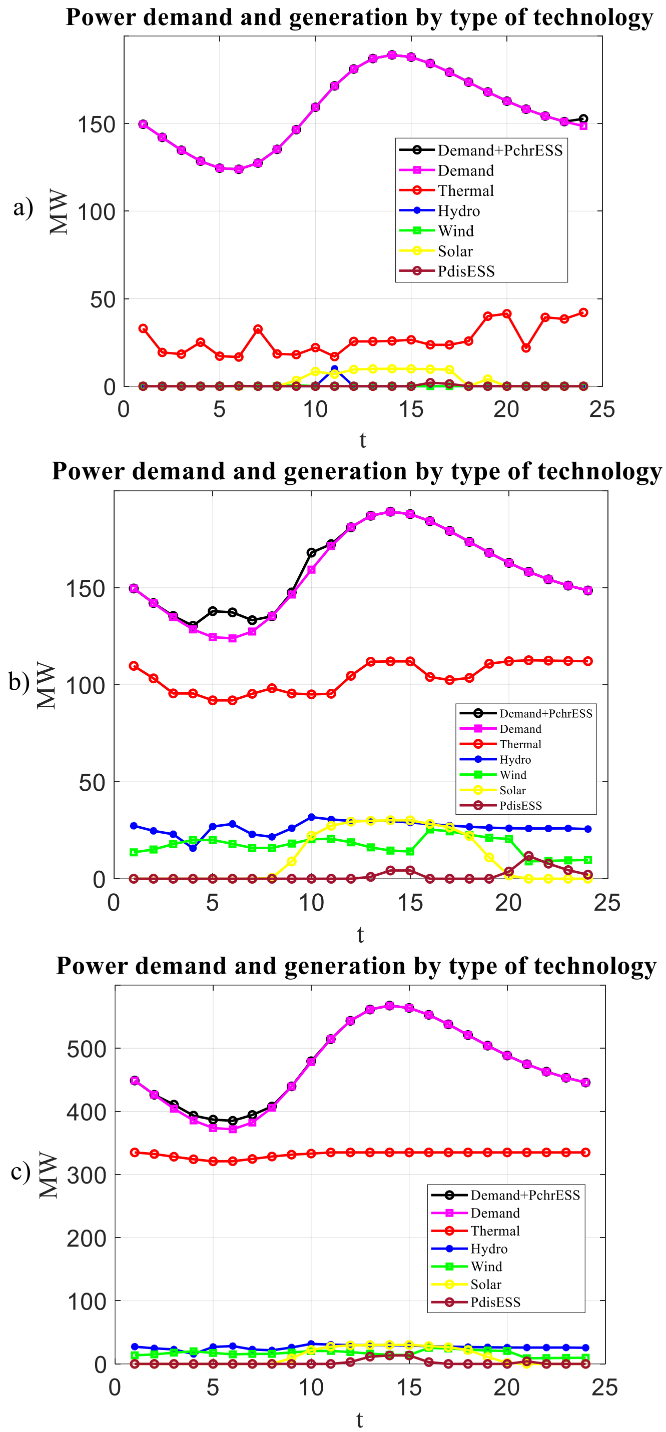

Fig. 1. Generation by type of technology and demand per hour. a) Case 1, b) Case 2, c) Case 3.

Fig. 1b indicates that, even though there is sufficient thermal capacity to supply the demand, not all thermal units are dispatched at max capacity due to their higher cost. Instead, renewable units operate preferentially due to their lower cost and it was not necessary to make load shedding. Fig. 1c shows as demand starts to rise (from period 8 onward), thermal generation becomes the predominant source, supplying 85% of total generation and maintaining a nearly constant output.

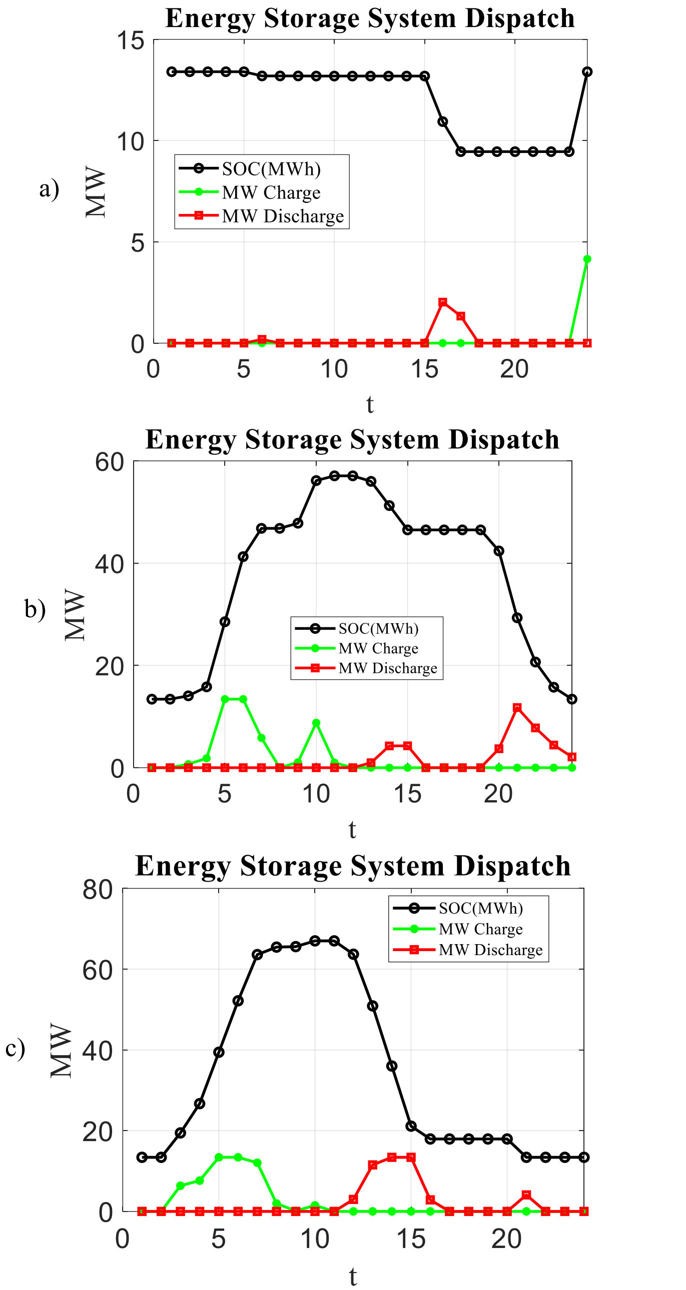

Fig. 2. ESS Dispatch and SOC per hour. a) Case 1, b) Case 2, c) Case 3.

The behavior of the ESS is illustrated in Fig. 2 for each study case. For case 1, Fig. 2a shows that the ESS is charged only in period 23, rather than during low-demand periods, because there is no optimization applied. Fig. 2b and Fig 2c shows, the ESS is charged primarily during low-demand periods with high renewable generation, when Local Marginal Prices (LMPs) are low. It is discharged during high-demand periods and lack of renewable generation help to reduce LMPs, as expected.

The initial and final SOC must be the same due to the constraint imposed (13.4 MW). When the ESS is loaded, in the SOC (black line) it is seen as an increase in stored energy and when it is unloaded as a decrease, where the highest amount of energy stored by the ESS was 57.07 in case 2 and 67.0 MWh respectively in case 3, (fully charged). Even though the ESS capacity is 67 MWh, operational constraints significantly reduce its effective production.

In case 1, the solution chooses to shed load in all time intervals, shedding 3067.202 MW out of the 3769.326 MW of total demand (81.37%), despite having enough generation to supply the demand, this result is correct due to incorporation of the load shedding model in the STHS problem and the lack of an economic penalty, as the solution is not optimized. This is shown in Fig. 3a.

In case 3, it is necessary to shed load at nodes 8, 14, 15, 17, 18, 19, 21, 26 and 30, in order to match the demand supply with the available generation and the transmittable power in the lines. This is depicted in Fig. 3b.

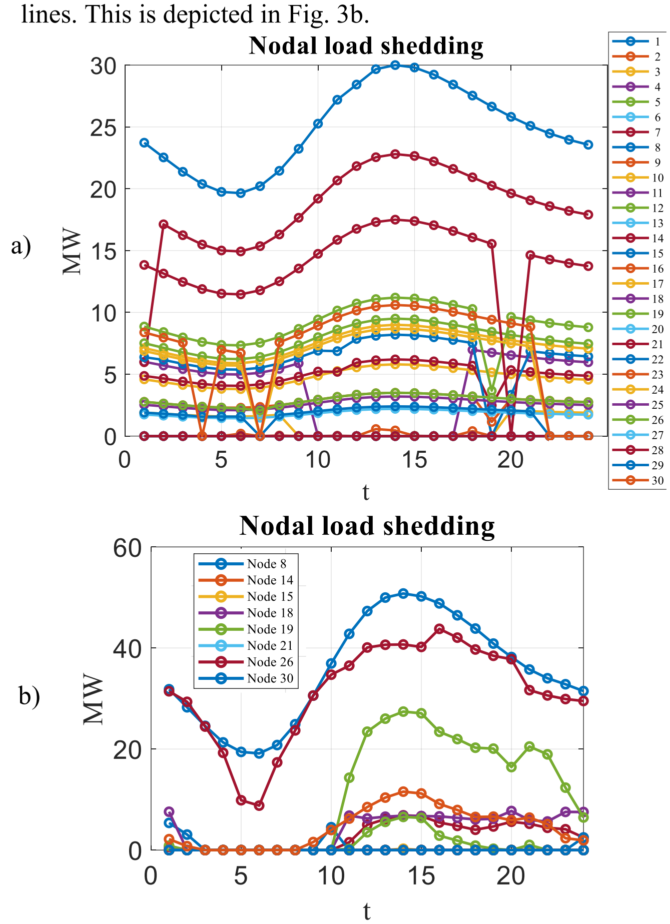

Fig. 3. Hourly nodal load shedding, a) Case 1, b) Case 3.

It can be observed in Fig. 4a, for case 2, the lowest Local Marginal Prices (LMPs) occur during hours 5 and 6 of 936.23 (\$/MWh). The highest LMPs occur in hour 14, 1198.7 (\$/MWh).

In case 3 the lowest LMPs occur in hours 8 and 9, 1612.1 (\$/MWh) in the nodes where no load shedding was performed which also coincide with the highest ESS charge period. In general, from hour 10 onward, all LMPs exceed 8500 (\$/MWh). The highest LMPs are in hours 10-22 of 10000 (\$/MWh), due to load shedding.

The status of volume, flow and spills are shown in Fig. 5 for each study case. In Fig 5a (Case 1), a high rate of spills in the reservoirs is observed, as the solution is not optimized. In Fig 5b (Case 2 and Case 3), the same behavior is observed, particularly for Unit 2, where spills occur. This is due to the fact that, since Units 1 and 2 are in series with Unit 3, and the amount of water being captured by the reservoirs per hour exceeds the flow constraint of Unit 3, the flow is limited to its maximum capacity, causing the excess water to spill. This issue could be addressed by adding an additional unit downstream of Units 1 and 2, near Unit 3.

Furthermore, since Unit 3 minimum flow is almost zero, in some time periods, its flow value is very close to zero. Despite the fact total capacities of the hydroelectric units are 40MW, the way they operate and the imposed constraints lead to a drastic reduction in production, significantly lowering their contribution to the system. It is observed that by having the total generation cost as the objective function, and given that the generation costs associated with the hydroelectric units are low compared to those of the other technologies, and with a constant water inflow in the reservoir throughout all time periods, the generation contribution from the hydroelectric units remains constant and is conditioned by the numerous constraints imposed on the system.

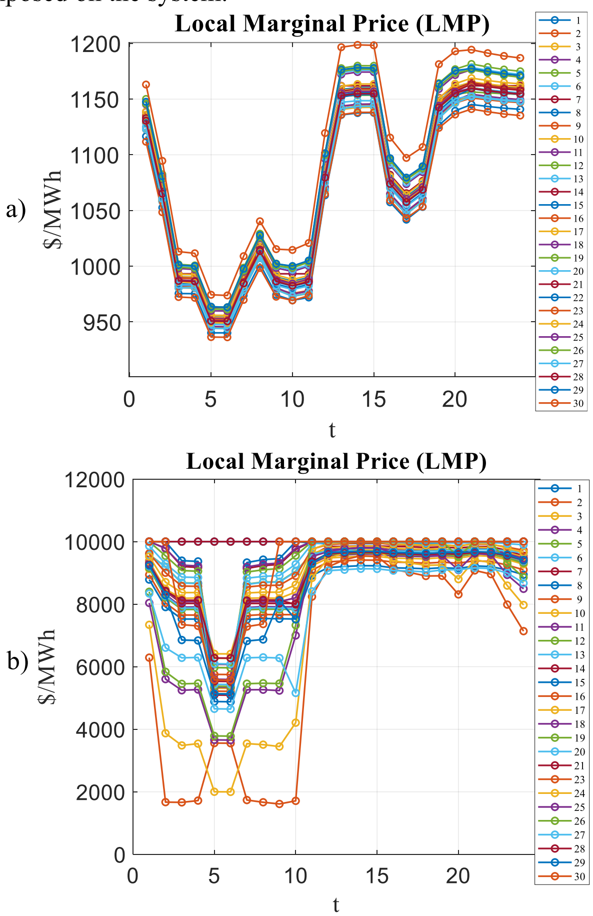

Fig. 4. Marginal local prices per hour. a) Case 2, b) Case 3.

VIII. Conclusion

In this paper the formulation and simulation of a STHS using nonlinear programming for a day ahead horizon, incorporating artificial neural networks (ANN) for demand forecasting is presented. The integration of wind and solar photovoltaic generation, ESS and cascaded hydroelectric power plants is considered, along with the transmission grid and load shedding models, all within a single optimization problem. The objective is to minimize generation costs and optimize power usage. Therefore, this work focuses on integrating all these elements into a single optimization problem to obtain the global optimal solution and efficiently dispatch the units. Three cases are validated: one without optimization and two optimized cases, one representing normal operation and another involving load shedding. The formulation is validated using the IEEE 30-node system, obtaining optimal solutions in all optimized scenarios. All variables and constraints remained within their limits, demonstrating that this methodology effectively finds the optimal solution without the need to relax any constraints at any point.

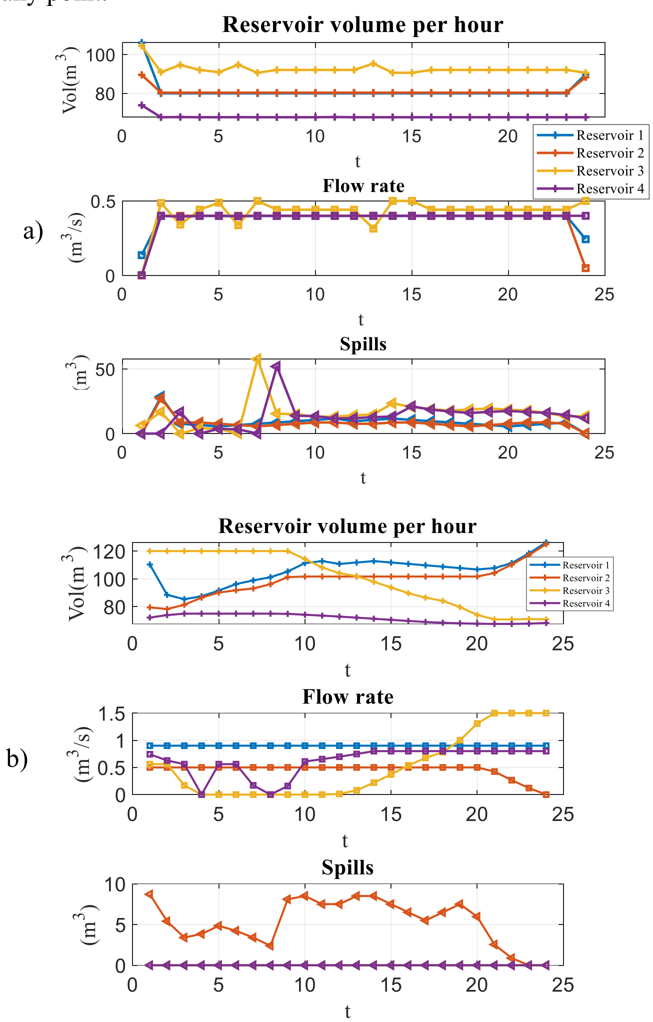

Fig. 5. Hydro cascade power plant system. a) Case 1, b) Case 2 and 3.

Small water spills occur due to the capacities and constraints imposed on this hydroelectric system. When the generation is insufficient and transmission line congestion arises, load shedding takes place, so LMPs increase drastically compared to case 3. In general, LMPs in Case 1 are directly influenced by thermal generation, as it is the most expensive source, while in

Case 3, they are significantly affected by the load shedding penalty of 10,000 $/MW.

Future research lines include to compare the proposed formulation with different algorithms to find the optimal solution, linearizing the quadratic terms, and testing the formulation in power systems with a larger number of nodes, real noisy conditions and greater hydroelectric generation capacity. Additionally, future work will focus on incorporating more ESS and exploring various scenarios that may arise in the real time operation of a PES.

APPENDIX

The data from the thermal and hydroelectric generators is presented in Table II-III. The modified IEEE 30-node test system in Fig. 6.

TABLE II
THERMAL GENERATORS DATA

Gen	RU_g MW	RD_g MW	$P_{g,t0}$ MW	$Q_{g,t0}$ MVAr
1	40	40	41.542	-5.4364
2	40	40	55.402	1.6748
3	25	25	22.74	34.197
4	27.5	27.5	39.909	31.754
5	15	15	16.267	6.9598
6	20	20	16.2	35.93

TABLE II (CONTINUATION)
THERMAL GENERATORS DATA

Gen	P_{min}	P_{max}	Q_{min}	Q_{max}	α	β	γ
	MW		MVAr				
1	0	80	-20	150	0	2	0.02
2	0	80	-20	60	0	1.75	0.0175
3	0	50	-15	62.5	0	1	0.0625
4	0	55	-15	48.7	0	3.25	0.00834
5	0	30	-10	40	0	3	0.025
6	0	40	-15	44.7	0	3	0.025

TABLE III
HYDROELECTRIC GENERATORS DATA

Unit	C1	C2	C3	C4	C5	C6	Vol_{min}	Vol_{max}
1	-0.0042	-0.42	0.030	0.90	10.0	-50	80	130
2	-0.0040	-0.30	0.015	1.14	9.5	-70	30	130
3	-0.0016	-0.30	0.014	0.55	5.5	-40	50	120
4	-0.0030	-0.31	0.027	1.44	14.0	-90	40	75

TABLE III (CONTINUATION)
HYDROELECTRIC GENERATORS DATA

Unit	q_{min}	q_{max}	Ph_{min}	Ph_{max}	Delay τ	Cost ($/MW)
1	0.001	0.9	0	10	2	0.1
2	0.001	0.5	0	10	1	0.1
3	0.001	1.5	0	10	4	0.1
4	0.001	0.8	0	10	0	0.1

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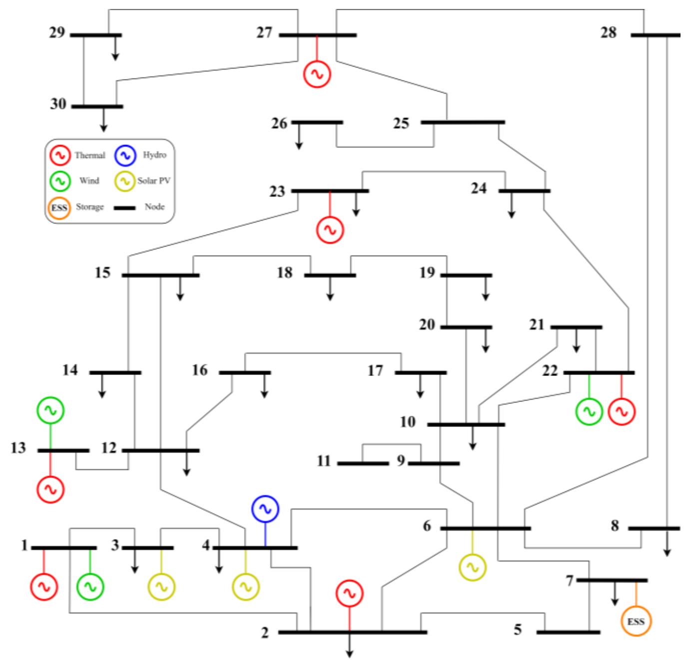

Fig. 6. Modified IEEE 30-node test system.

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